Chan, H. K., Wang, X., Lacka, E., & Zhang, M. (2016). A mixed-method approach to extract the value of social media data. *Production and Operations Management*, *25*(3), 568–583. https://doi.org/10.1111/poms.12390

<u>**Cover Page**</u>

A Mixed-Method Approach to Extracting the Value of Social Media Data

Hing Kai Chan[#]
Nottingham University Business School China,
University of Nottingham Ningbo China,
Ningbo 315100, China.
Tel: +86 574 8818 0964
Email: hingkai.chan@nottingham.edu.cn

Xiaojun Wang
Department of Management,
University of Bristol,
Bristol BS8 1TN, UK.
Tel: +44 (0)117 3310789
Email: xiaojun.wang@bristol.ac.uk

Ewelina Lacka
Business School,
University of Strathclyde,
Glasgow G4 0QU, UK.
Tel: +44 (0)141 548 4801
Email: ewelina.lacka@strath.ac.uk

Min Zhang
Norwich Business School,
University of East Anglia,
Norwich NR4 7TJ, UK.
Tel: +44 (0)1603 59 7386
Email: m.zhang1@uea.ac.uk

#Corresponding author

Abstract

In the last decade, social media platforms have become important communication channels between businesses and consumers. As a result, a lot of consumer-generated data are available online. Unfortunately, they are not fully utilised, partly because of their nature: they are unstructured, subjective, and exist in massive databases. To make use of these data, more than one research method is needed. This study proposes a new, multiple approach to social media data analysis, which counteracts the aforementioned characteristics of social media data. In this new approach the data are first extracted systematically and coded following the principles of content analysis, after a comprehensive literature review has been conducted to guide the coding strategy. Next, the relationships between codes are identified by statistical cluster analysis. These relationships are used in the next step of the analysis, where evaluation criteria weights are derived on the basis of the social media data through probability weighting function. A case study is employed to test the proposed approach.

Keywords: Social media, mixed-method, product innovation, business intelligence, analytics.

Received: January 2014; accepted: April 2015 by Jason Choi after four revisions.

1. Introduction

Recent decades have witnessed a new trend in Operations Management (OM) research, with the number of empirical-studies steadily growing (e.g. Flynn *et al.*, 1990; Scudder and Hill, 1998). This trend supplements traditional OM research, which was dominated by mathematical/analytical approaches (Fortun and Schweber, 1993), and can help to address contemporary research needs (Singhal and Singhal, 2012). These needs are directly linked to new research opportunities arising from the rapid development of digital technologies (i.e. the Internet), which enable researchers to collect valuable data online. Unfortunately, these data are not always well-structured. On the contrary, online data generated by the end consumer are often qualitative and highly unstructured. As a result, OM researchers are hardly able to apply a homogenous approach to utilise it. In order to analyse data collected on the Internet, multiple research methods are required, which, while drawing from different disciplines, will explore the true value of online data. Those multiple methods of so-called ‘Big Data’ analysis should not only employ OM data analysis techniques, but also combine them with techniques used in disciplines such as marketing or management, which are well-known for their end consumer empirical, and sometimes qualitative, data analysis. Such multiple approaches allow researchers not only to address the need to make use of online data, but also incorporate interdisciplinary knowledge into OM research. Furthermore, the multiple approaches to social media data analysis also allow researchers to respond to recent call for data-driven research in the OM discipline (Simchi-Levi, 2014). This is the first study to propose such a mixed-method approach to handle qualitative social media data for quantitative decision-making.

Section 2 of this study presents a review of social media data research, and Section 3 provides a detailed summary of the above-mentioned data analysis steps. In Section 4, a case study is employed which tests the proposed mixed-method approach for new product development decision-making. The case study is based on data extracted from the SAMSUNG Mobile Facebook page (https://www.facebook.com/SamsungMobile), and is therefore used to develop a product innovation model for smartphone devices. The study concludes with Section 5.

2. Social Media Data Research

2.1 The nature of social media data

Social media platforms have many forms, and therefore a number of definitions of social media data exist. To clearly delineate the scope of this research, we consider social media data to comprise of those comments posted by users on social network sites, defined by Ellison (2007) as “web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system. The nature and nomenclature of these connections may vary from site to site”. Accordingly, social media sites serve as platforms for sharing and exchanging information, (i.e. social media data (Akar and Topçu, 2011)).

Social media data are freely available. Collecting it does not require effort or a budget (Hanna *et al.*, 2011). The data are supplied by end users (i.e. customers) who voluntarily share their views and opinions online in the form of qualitative comments (Xiang and Gretzel, 2010). Utilising these comments for business and research purposes, however, is not satisfactory. Gu and Ye (2014) report that, to date, "little research has been done to understand how management should respond to customer reviews in online social media". Thus, more effort has to be put into the analysis of end users' comments in order to fully explore the potential of the data. This has recently become particularly important as it is predicted that consumer power will rise due to the availability of social media sites (Labrecque *et al.*, 2013). Thus, companies should not ignore the importance of social media platforms and the value of social media data. On the contrary, they should find an efficient and effective way to analyse and interpret such data in order to react to the information it contains in a timely manner. This, however, is not an easy task due to the inherent pitfalls of social media data – the unstructured, qualitative and subjective views and opinions of end consumers posted on social media platforms (Jang *et al.*, 2013; Malthouse *et al.*, 2013).

Some researchers claim that the above drawbacks can be effectively addressed by systematic analysis of social media datasets, where a hierarchical model is employed to group online comments (Anderson and Joglekar, 2005; Tripathy and Eppinger, 2013). However, defining such a hierarchical model for social media data is a challenge, which this study sets out to address. In particular, this study aims to develop a hierarchical model and test it for a decision-making process in which social media data are used for new product development.

2.2 Social media data and new product development

Over the last two decades, global competition and continuous consumer demand for new, innovative products and services have compelled companies to continually invest in new product development (NPD). Successful NPD provides companies with an indispensable opportunity to gain competitive advantage and sustain long-term organisational survival (Henard and Szymanski, 2001; Krishnan and Ulrich, 2001). Acquiring information from potential end customers about their product requirements, preferences and needs is often cited in the literature as a key factor for successful NPD (Von Hippel, 1986; Katila and Ahuja, 2002; Piller and Walcher, 2006). Thus, many researchers (Nambisan, 2002; Hoyer *et al.*, 2010; Fuchs and Schreier, 2011) promote the idea of empowering customers to take a much more active role in the NPD process. This has become more feasible on online (i.e. social media) platforms , where consumers are provided with a "sense of empowerment" (Hoyer *et al.*, 2010) so that they can interact and exchange their views and opinions about the existing product online, while influencing NPD at the same time (Nasbisan, 2002; Sawhney *et al.*, 2005; Piller and Walcher, 2006; Füller *et al.*, 2006).

These online interactions and exchanges of comments online have become a point of interest for NPD researchers. Nasbisan (2002), for instance, develops a theoretical model of customers' NPD roles (i.e. source and user, or co-creator) in a virtual environment. By comparing it to a traditional perspective on customer involvement in new product development, Sawhney (2005) examines how the Internet can serve as a powerful platform for collaborative innovation with customers. Piller and Walcher (2006) propose Internet-based toolkits for idea competition, in order for manufacturers to access innovative ideas and solutions from users. Through a case study of Audi, Füller *et al.* (2006) illustrate the applicability of online communities as a platform for customer interaction in order to attain valuable input for NPD.

Despite this noticeable increase in the use of digital technologies to engage customers in the NPD process, very limited attention has been given to social media platforms as a means of extracting customer-generated data to support the NPD process. The study attempts to fill this gap while accomplishing two goals. First, it aims to develop a hierarchical model which, by drawing from different research disciplines, is able to extract true value from end consumer data. Second, it aims to test a developed model for NPD decision-making employing social media data.

2.3 Quantifying social media data

In order to accomplish the first objective of this study and develop a new hierarchical model for social media data analysis, social media data, in the form of consumer generated comments, is systematically coded. This part of the research is exploratory, and is thus facilitated by content analysis, a widely used research method in marketing and management disciplines to analyse qualitative datasets (Carley, 1993; Hsieh and Shannon, 2005; Davies and Joglekar, 2013). This technique is also employed in many social media research studies to convert codified information into a more usable format (e.g. Denecke and Nejdl, 2009; Li et al., 2011).

In line with the principles of content analysis, prior to the analysis of a social media dataset a list of codes is created, based on a comprehensive literature review of the research field. This approach to coding is selected as it is believed to be more objective and more comprehensive than, for example, an expert opinion, or a survey from a consultancy. The list of factors, or codes, serves as a guideline for the social media data coding.

At this stage the limitations of social media data, for example its lack of structure or its subjectivity, must be overcome in order to accurately interpret it and thus extract its actual value (Trusov *et al.*, 2009). To achieve this goal, statistical cluster analysis is conducted to form a hierarchical decision-making model. Through cluster analysis, similar codes are grouped together for later decision-making analysis. This procedure is called relational analysis, and is similar to the decomposition method for conceptual product design proposed by Mullens *et al.* (2005). Although Mullens *et al.* (2005) make use of the "Quality Function Deployment" model, and this research makes use of the Multi-Criteria Decision-Analysis (MCDA) method, the final output of both methods is similar. This is confirmed by Anderson and Joglekar (2005), who also use a hierarchical model for NPD.

Next, the frequency of occurrence of the codes, which "reflects the degree of emphasis placed on that concept" (Davies and Joglekar, 2013), is utilised as the input to a probability weighting function (PWF) to calculate their decision weights. PWF permits a non-linear transformation of probabilities into decision weights, and is an essential feature of several utility theories including rank-dependent models and prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Prelec, 1998). Consequently, on the basis of the content analysis, a hierarchical model is formed by means of the clusters. The corresponding importance weight between factors is evaluated using the PWF, as discussed above. An MCDA method is then applied to evaluate alternative new product designs.

Based on the above procedure, this study proposes a mixed-method approach to address the challenge of extracting the true value of social media data for decision-making. There are a number of theoretical and managerial implications in doing so. First, the proposed approach for social media data mining overcomes the limitations of data generated by end consumers on social media platforms, converting it to useful information for decision-makers. Moreover, it applies the PWF with regards to social media data. Finally, this is the first study which uses social media data (i.e. customer inputs) to help construct a decision-making model for NPD. The details of the integrated methodology are discussed in Section 3.

3. Research methodology

As discussed in Section 2, the proposed approach to social media data analysis incorporates the following steps: a comprehensive literature review, content analysis of social media data; a probability weighting function; and a MCDA method. The proposed procedure is presented in Figure 1 and its details are discussed in the subsequent sections below.

3.1 Codes generation

A literature review is defined by Fink (1998) as "a systematic, explicit, and reproducible design for identifying, evaluating, and interpreting the existing body of recorded documents". Tranfield *et al.* (2003) argue that systematic reviews could provide practitioners and policy-makers with a reliable basis to formulate decisions and take action through enhancing the legitimacy and authority of the subsequent evidence. From a methodological point of view, Brewerton and Millward (2001) believe that literature reviews can be as comprehensive as content analysis. Furthermore, the literature review has been found to be a useful tool to identify patterns and themes, as well as conceptual contents of the research field (Seuring and Muller, 2008). Consequently, a comprehensive literature review is a reliable means to identify key themes in a field of study, which in turn can guide qualitative data analysis.

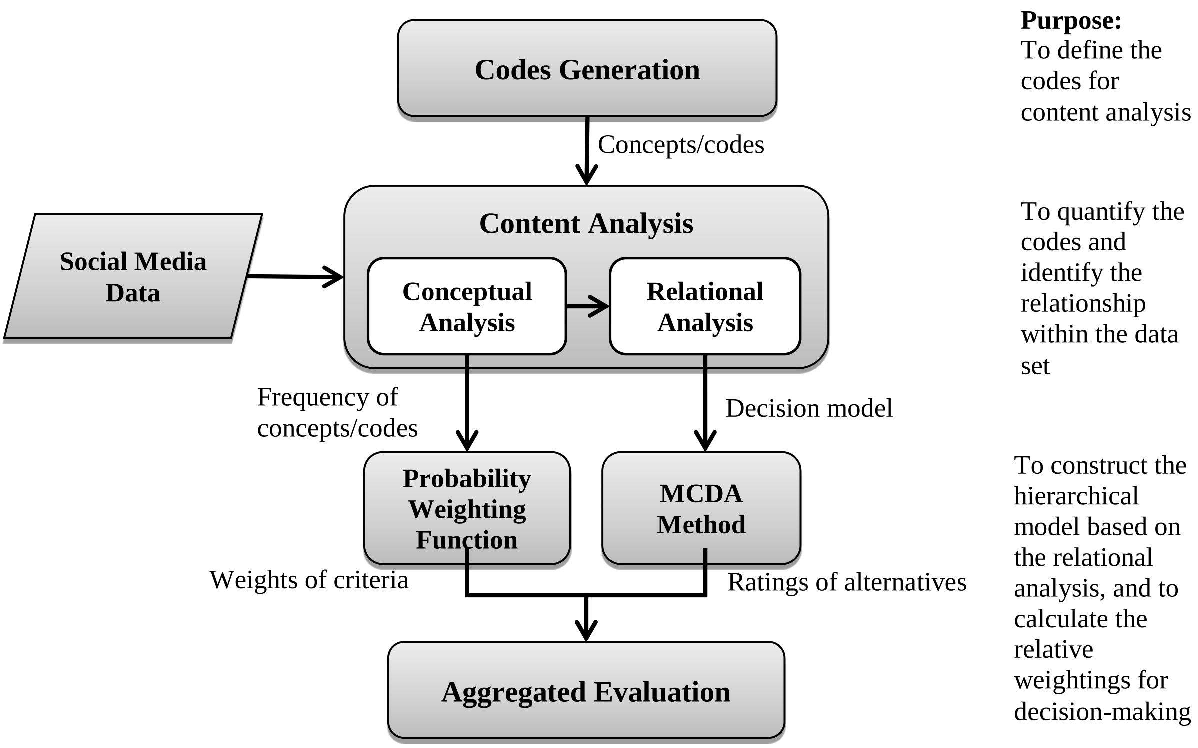

Figure 1. Illustration of proposed methodology

In this approach to social media data analysis a comprehensive literature review is used to identify key themes relevant to product innovation management and, later, factors related to each theme. The identified factors will be used as codes for the content analysis of the social media data set. This first step of the proposed approach is of particular importance, as it aims to organise data according to codes identified in the literature, thus addressing the limitations of social media data deriving from its unstructured nature.

3.2 Content analysis of social media data

Although factors identified on the basis of a literature review are often used as decision model constructs, in this study they are used as codes for content analysis and further cluster analysis. This aims to preserve consumers' 'sense of empowerment', where consumers' views and opinions are taken into consideration when developing new research models. Thus, by incorporating content analysis of social medal data in the development of the decision model, this research addresses the limitations of previous models, which do not consider consumer input into decision-making.

The content analysis consists of two parts. The first, conceptual analysis, is used to establish the existence and frequency of factors in the dataset, and thus involves the selective reduction of comments into meaningful units (codes). It is followed by the second part, relational analysis, which examines relationships between codes. In order to statistically verify these relationships, the Pearson Correlation Coefficient is used to represent the similarity indexes between pairs of factors. The complete linkage clustering approach, one of the hierarchical clustering methods, is employed to evaluate the data based on the similarity and frequency of occurrence (so called the "distance" between clusters) when clusters are combined. Initially, each factor is in a cluster of its own, and then clusters with the shortest "distance" are merged (Peng and Liu, 2015). The outcome of this part is a hierarchy of clusters, which can then be adopted for later MCDA.

3.3 Weights calculation using the probability weighting function (PWF)

After the relational analysis, it is imperative to measure the importance of decision factors based on the social media dataset. There are many weighting methods to facilitate this process including MCDA approaches such as Analytic Hierarchy Process (AHP) or Analytical Network Process (ANP), and text representation approaches such as term frequency/inverse document frequency (TF-IDF) or Latent Sematic Indexing (LSI). In this research, the probability weighting function (PWF) is used to calculate the weights of evaluation criteria.

A PWF, $w(p)$, allows probabilities to be weighted non-linearly. Previous empirical studies of the weighting function show that $w(p)$ is regressive (first $w(p) > p$, then first $w(p) < p$), s-shaped (first concave and then convex), and asymmetrical (Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Prelec, 1998). There are many versions of PWF. In this study, Prelec (1998) PWF is adopted and is expressed as:

$$w(p) = \exp(-(-\ln p)^{\alpha}) \qquad (1)$$

Here, $p \in [0,1]$ is the probability of occurrence of a relevant factor in the studied dataset, and α ($0 < \alpha < 1$) is the standard parameter in PWF. The Prelec (1998) PWF has the following merits: parsimony; consistency with much of the available empirical evidence; and an axiomatic foundation. For a decision criterion, C_i, that contains n items, the criterion weight can be calculated as:

$$w_i = \sum_j w(p_{ij}), \; j = 1,2,\cdots,n \qquad (2)$$

in which p_{ij} is the probability of concurrence of j^{th} item in criterion C_i.

This method is particularly useful for assigning a weight to each criterion while analysing social media data, because it does not require an individual decision-maker to rank the criteria. As a result, decision makers can use real data from end consumers to calculate the weights. In comparison to other MCDA approaches, which require expert judgement in determining relative weightings, this is a more effective weighting technique, since the calculation is based on frequency of occurrence of relevant user comments. Moreover, it is more appropriate in studies that aim to retain a "consumer sense of empowerment" in the decision-making process.

3.4 Evaluating alternatives using MCDA methods

After constructing a decision model and estimating evaluation criteria weights, the preference between alternative options has to be determined. In order to incorporate all the decision criteria in the evaluation, it is essential to know how good one alternative is over another in relation to a particular evaluation criterion. At this stage many MCDA methods can be applied, such as AHP, fuzzy AHP, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and so on. However, without Steps 3.1 to 3.3 outlined in previous sub-sections, one is unable to apply the methods for making any decisions. This is also the main contribution of this paper.

AHP, developed by Saaty (1980), is the most widely used technique for multiple criteria analyses. Its fuzzy extension, fuzzy AHP (Van laarhoven and Pedrycz, 1983; Buckley, 1985), utilises the advantages of fuzzy set theory which can incorporate imprecise and/or uncertain variables to address the challenge of uncertainty and/or unknown data in operations decisions, for example product development or project management. Proposed by Hwang and Yoon (1981), the main concept of TOPSIS is to define the positive ideal solution and the negative ideal solution. The most preferred alternative should be closest to the positive ideal solution and furthest from the negative ideal solution. The mathematical procedures of the three MCDA methods have been well reported in the literature (Saaty, 1980; Van laarhoven and Pedrycz, 1983; Buckley, 1985; Hwang and Yoon, 1981; Chamodrakas *et al.*, 2009). The authors would like to stress that the proposed approach is not limited to using AHP, Fuzzy AHP or TOPSIS. The authors simply make use of them as demonstration, and results from these three methods are listed in the next section.

4. Case Study

In order to test the proposed approach to social media data analysis for NPD decision-making, social media data from the official Samsung Mobile Facebook page was extracted using the NCapture tool of NVivo 10 software. Two months' worth of data in the form of consumer comments were downloaded for the analysis; in total, 86,055 comments were downloaded. These ranged from general enquiries by Samsung consumers to queries related to a particular Samsung smart phone model, and included comments posted in all languages. In order to keep the focus of this research project on NPD, it was decided to extract comments related to the latest Samsung smart phone model, the Samsung Galaxy S4. To ensure a good understanding of the comments and thus accurate content analysis, only comments posted in English were considered, as English is the common language shared with the researchers. With this imposed control, 1,674 comments in English related to the Samsung Galaxy S4 model were used for the final analysis.

4.1 Selecting the proper factors for new product development

Many researchers have studied factors associated with NPD in a variety of settings. These studies adopt different perspectives and different sets of evaluation criteria. Nevertheless, among a considerable number of empirical research projects on NPD reported in the literature, the determinants of new product performance often involve some combination of product, strategic, development process, organisational and/or market environment elements (Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Cho and Lee, 2013). Therefore, this study adopts five concepts as the five main themes to which specific factors (codes) are integrated. Focusing on the relevant literature in the last twenty years, a comprehensive list of evaluation criteria was generated for the purpose of new product performance measurement. The review results are displayed in Table 1. The list of NPD factors is used as a guideline for conducting content analysis considering consumer input.

Table 1. Key factors of new product performance

Themes	Label	Factors	Description	Sources
Strategy	S1	Technological synergy	Congruency between the existing technological skills of the firm and the technological skills needed to successfully execute a new product initiative.	Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Pun *et al.*, 2010
	S2	Company resources	Focused commitment of personnel and R&D resources to a new product initiative.	Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Krishnan and Ulrich, 2001
	S3	Business strategy	This factor indicates the strategic impetus for the product development (e.g., defensive, reactive, proactive, imitative).	Montoya-Weiss and Calantone, 1994; Hultink *et al.*, 1997; Im and Workman, 2004
	S4	Marketing synergy	Congruency between the existing marketing skills of the firm and the marketing skills needed to successfully execute a new product initiative.	Montoya-Weiss and Calantone, 1994; Cooper and Kleinschmidt, 1995; Hultink *et al.*, 1997; Henard and Szymanski, 2001; Krishnan and Ulrich, 2001; Pun *et al.*, 2010
	S5	Innovation strategy	A plan made by an organisation to encourage advancements in technology or service by investing in research and development activities.	Hultink *et al.*, 1997
Development process	D1	Technical competitiveness	Proficiency of a firm's use of technology in a new product initiative.	Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Cho and Lee, 2013; Cankurtaran *et al.*, 2013
	D2	Marketing activities	Proficiency with which a firm conducts its marketing activities.	Montoya-Weiss and Calantone, 1994; Cooper, 1994; Cooper and Kleinschmidt, 1995; Henard and Szymanski, 2001; Cankurtaran *et al.*, 2013
	D3	Protocol	Protocol refers to the firm's knowledge and understanding of specific marketing and technical aspects prior to product development.	Montoya-Weiss and Calantone 1994; Cankurtaran *et al.*, 2013
	D4	Speed to market	Speed in the concept-to-introduction time line (i.e., time to market).	Cooper and Kleinschmidt, 1994; Padmanabhan, 1997; Hendricks and Singhal, 1997; Gruner and Homburg, 2000; Henard and Szymanski, 2001; Krishnan and Ulrich, 2001; Chen *et al.*, 2005; Mallick and Schroeder, 2005
	D5	Financial/business analysis	The proficiency of ongoing financial and business analysis during development,	Montoya-Weiss and Calantone, 1994; Cooper,

			prior to commercialisation and full-scale launch.	1994; Carrillo, 2005
	D6	Cost	Development cost, including measures of production, R&D or marketing cost overruns or expenditures.	Cooper, 1994; Carrillo, 2005; Chen *et al.*, 2005; Mallick and Schroeder, 2005; Pun and Chin, 2005
	D7	Design and testing	Product design, and performance testing and validation.	Krishnan and Ulrich, 2001; Pun and Chin, 2005; Cankurtaran *et al.*, 2013
	D8	Process development and improvement	Employment of formalised product development procedures.	Pun and Chin, 2005; Pun *et al.*, 2010
	D9	Well-defined plan/roadmap	Well-defined plan roadmap to developing new product(s).	Cooper and Kleinschmidt, 1995; Carrillo, 2005; Pun and Chin, 2005; Cho and Lee, 2013
	D10	Customer input	Incorporation of customer specifications into a new product initiative	Henard and Szymanski, 2001; Ernst, 2002;Pun *et al.*, 2010; Cankurtaran *et al.*, 2013
	D11	Product launch	Proficiency with which a firm launches the product	Hendricks and Singhal, 1997; Hultink *et al.*, 1997; Padmanabhan *et al.*, 1997; Gruner and Homburg, 2000; Henard and Szymanski, 2001; Krishnan and Ulrich 2001;
	D12	Process concurrency	Synchronization of activities of multiple processes, requireing good communication between processes.	Chen *et al.*, 2005; Cankurtaran *et al.*, 2013
Market environment	M1	Market potential	Anticipated growth in customers/customer demand in the marketplace.	Montoya-Weiss and Calantone, 1994; Hultink *et al.*, 1997; McGrath, 1997; Boer, 1998; Henard and Szymanski, 2001
	M2	Market competition	Degree, intensity or level of competitive response to a new product introduction.	Montoya-Weiss and Calantone, 1994; Hultink *et al.*, 1997; Slater and Narver, 1998; Henard and Szymanski, 2001; Cankurtaran *et al.*, 2013
	M3	Market turbulence	The factor refers to the rate of change in the composition of customers' needs and preferences.	Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Carrillo, 2005; Chen *et al.*, 2005; Pun *et al.*, 2010
	M4	Entry barriers	The factor refers to obstacles that make it difficult to enter a given market.	Slater and Narver, 1998; Cho and Lee, 2013; Cankurtaran *et al.*, 2013
	M5	Customer needs	Expectations and requirements from customers when purchasing the product.	Mishra *et al.*, 1996; Henard and Szymanski, 2001; Pun and Chin, 2005; Cho and Lee, 2013
	M6	Legal regulation	This factor refers to regulations that could affect the product development, e.g. environmental issues.	Cho and Lee, 2013
	M7	Technological turbulence	This factor refers to the rate of change associated with technology used to develop new products in an industry.	Chen *et al.*, 2005; Cankurtaran *et al.*, 2013
Organisational	O1	Internal and external relations	This factor refers to the coordination and cooperation within and between firms.	Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Carrillo, 2005; Pun and Chin, 2005; Cankurtaran *et al.*, 2013
	O2	Communication	Level of communication among the team	Henard and Szymanski, 2001;

			and across departments in a new product initiative.	Ernst, 2002; Pun and Chin, 2005
	O3	Experience and competencies	An organisation's experience and alignment with core competencies.	Cankurtaran *et al.*, 2013
	O4	Organisational support	Degree of senior management support for a new product initiative.	Montoya-Weiss and Calantone, 1994; Souder and Song, 1998; Henard and Szymanski, 2001; Ernst, 2002; Bastic, 2004; Cankurtaran *et al.*, 2013
	O5	Organisational integration	Degree of multiple-department participation in a new product initiative.	Ernst, 2002; Chen *et al.*, 2005; Cankurtaran *et al.*, 2013
	Q6	Organisational structure	This includes measures of organisational climate, size, centralisation, reward structure and job design.	Montoya-Weiss and Calantone, 1994; Pun and Chin, 2005; Cankurtaran *et al.*, 2013
Product	P1	Quality	The product's ability to perform its primary function.	Gruner and Homburg, 2000; Pun and Chin, 2005;
	P2	Product advantage	Superiority and/or differentiation over competitive offerings.	Montoya-Weiss and Calantone, 1994; Hultink *et al.*, 1997; Henard and Szymanski, 2001; Pun and Chin, 2005
	P3	Product price	Perceived price-performance congruency (i.e. value).	Hultink *et al.*, 1997; Henard and Szymanski, 2001
	P4	Product meets customer needs	Extent to which a product is perceived to satisfy the desires/needs of the customer.	Gruner and Homburg, 2000; Henard and Szymanski, 2001
	P5	Product technological performance	Perceived technological sophistication (e.g., high-tech, low-tech) of the product.	Gruner and Homburg, 2000; Henard and Szymanski, 2001; Mallick and Schroeder, 2005
	P6	Product innovativeness	Perceived newness/originality/uniqueness/ radicalness of the product	Hultink *et al.*, 1997; Henard and Szymanski, 2001

4.2 Content analysis results

For the purpose of this research a two-step content analysis was carried out, as described in Section 3.2 above. First, the conceptual analysis was conducted. Factors revealed during the comprehensive literature review served as codes to guide the conceptual analysis. Next, to avoid subjectivity of the analysis, the definition of each factor/code was provided (see Table 1).

Prior to the analysis, the researchers became familiar with all factors/codes and their definitions. The researchers then discussed the coding strategy and reached a consensus on the most suitable approach. It was decided to carry out the analysis using manual coding. It is believed that for the purpose of this study, a manual approach to coding was more appropriate than any intelligence techniques as it allows, once again, for consumers' "sense of empowerment" to be sustained. Prior to final coding, the sample data was analysed by all researchers, and results were discussed in an effort to ensure reliability and validity of the final analysis. The researcher conducting the conceptual analysis has extensive knowledge and skills in carrying out qualitative research.

Following this methodology, data in the form of consumer-generated comments extracted from Samsung Mobile's Facebook page were analysed. Each comment was analysed individually. The conceptual analysis of 1,674 comments revealed the following frequency of concepts (see Table 2). This serves as a base for a hierarchical evaluation model.

Table 2. Summary of the coded factors according to Table 1

Name	Frequency	Name	Frequency
Business strategy	2	Organisational integration	0
Communication	672	Organisational structure	7
Company resources	0	Organisational support	164
Consumer input	144	Process concurrency	0
Consumer needs	771	Process development and improvement	2
Cost	1	Product advantage	144
Design and testing	10	Product innovativeness	205
Entry barriers	1	Product launch	5
Experience and competencies	0	Product meets consumer needs	765
Financial/business analysis	5	Product price	143
Innovation strategy	0	Product technological performance	279
Internal and external relations	0	Protocol	2
Legal regulations	40	Quality	761
Market turbulence	6	Speed to market	133
Market competition	142	Technical competitiveness	1
Market potential	15	Technological synergy	304
Marketing activities	22	Technological turbulence	2
Marketing synergy	0	Well-defined plan/roadmap	2

In the coding process, it was possible to code one comment using multiple codes, as presented in the following examples:

1. *'Brother plz tell me the update price of galaxy s3 and s4 16 GB version.if there is any kind of guarantee plz tell me!!'*

- Technological synergy –*'update price of galaxy s3 and s4 16 GB version'* – the consumer recognises congruency between the Samsung Galaxy S3 model and the Samsung Galaxy S4 model.
- Legal regulation – *'any kind of guarantee'* – the consumer asks about legal restrictions related to product guarantee
- Product price – *'tell me the update price'* – consumer asks about the product price

2. *'How do I use the video calling on my S4 mini please'*

- Communication – *'How do I use the video calling on my S4 mini please'* – consumer encourages communication with the company
- Product Advantage – *'the video calling on my S4 mini'* – consumer comments on product feature
- Product Technological Performance – *'use the video calling'* – consumer comment relates to product performance
- Product Innovativeness – *'video calling'* – consumer refers to new innovative feature

Following the conceptual analysis, relational analysis was carried out to examine relationships between concepts with statistical accuracy. At this stage, cluster analysis was employed with the help of NVivo 10 software. The significant results of cluster analysis, assessed on the basis of the Pearson Correlation Coefficient test and scoring 0.9 or above, are presented in Table 3.

As can be seen from the results above, all factors (codes) of new product development are analysed for correlation with each other. Interestingly, when looking at individual factors it is obvious that not all factors are highly correlated with each other. The most closely correlated factors come from the 'Product' category: namely 'Quality'; 'Product advantage'; 'Product price'; 'Product meets consumer needs'; 'Product technological performance'; and 'Product innovativeness'. Those items are correlated with two items from the 'Organisational' category: 'Communication' and 'Organisational support'. The third category in which items are correlated with the above-mentioned factors is 'Market environment': the correlated items are 'Market competition'; 'Entry barriers'; 'Consumer needs'; and 'Legal regulations'. It was further found that the items within the 'Organisational' category, especially 'Communication' and 'Organisational support', are also correlated with each other. Finally, 'Technical competitiveness' within the 'Development process' category and 'Technological synergy' in the 'Strategy' category are also highly correlated.

Table 3. Pearson correlation test of the cluster analysis (partial results)

Category	Category	Pearson correlation coefficient
Technical competitiveness	Entry barriers	1
Product meets consumer needs	Consumer needs	0.998179
Product advantage	Market competition	0.993339
Product technological performance	Product innovativeness	0.982170
Quality	Communication	0.974065

Product technological performance	Product meets consumer needs	0.970961
Product technological performance	Consumer needs	0.969917
Quality	Consumer needs	0.969344
Quality	Product meets consumer needs	0.968672
Product technological performance	Communication	0.966433
Consumer needs	Communication	0.963858
Product meets consumer needs	Communication	0.963807
Quality	Product technological performance	0.960613
Product technological performance	Consumer input	0.959929
Product innovativeness	Consumer input	0.954355
Product meets consumer needs	Product innovativeness	0.953120
Product innovativeness	Consumer needs	0.950787
Quality	Product price	0.950493
Quality	Organisational support	0.944644
Product innovativeness	Communication	0.943133
Product advantage	Consumer needs	0.942616
Product meets consumer needs	Product advantage	0.942462
Quality	Product advantage	0.940823
Technological synergy	Speed to market	0.938727
Product technological performance	Product advantage	0.938218
Consumer input	Communication	0.936907
Product price	Consumer needs	0.935859
Product price	Organisational support	0.935111
Product meets consumer needs	Consumer input	0.934062
Product meets consumer needs	Market competition	0.933809
Market competition	Consumer needs	0.933606
Product price	Product meets consumer needs	0.932992
Consumer needs	Consumer input	0.931519
Quality	Market competition	0.931010
Product technological performance	Market competition	0.927522
Technological synergy	Communication	0.925753
Quality	Consumer input	0.924078
Product price	Product advantage	0.921377
Technological synergy	Consumer input	0.918934
Product advantage	Organisational support	0.918029
Quality	Product innovativeness	0.917551
Product price	Market competition	0.916997
Technological synergy	Product technological performance	0.914125
Product innovativeness	Product advantage	0.913672
Organisational support	Market competition	0.913360
Product technological performance	Product price	0.910524
Product price	Communication	0.909790
Product advantage	Communication	0.905783
Product innovativeness	Market competition	0.904221
Technological synergy	Product innovativeness	0.902046

On the basis of the Pearson Correlation Coefficient test, it can be observed that consumers pay attention to a product when making their purchase decision. In particular, consumers are interested in ‘value for money’. They are looking for quality products with features and advanced technology to meet their growing needs. Further, they consider it important to maintain good communication with the company, and to receive post-purchase support in the form of consumer service, which should be guaranteed. Finally, it is revealed that consumers look for highly innovative products, and are aware of competition in that market.

So far, the social media data analysis of the case study makes it apparent that Samsung, while focusing on the development of new products with advanced technology, is likely to meet consumers' needs and sustain its market position. Effective communication with its consumers and provision of high-quality consumer service is also indicated as a key to competitive advantage. A hierarchical decision model can be developed based on the similarities among, and frequency of occurrence of, the decision factors, which is illustrated in Figure 2.

The advantage of such an analysis is that the number of evaluation criteria can be reduced by removing the items that are not relevant to the selected product, and grouping items that show a high positive relationship with one evaluation criterion. For instance, 'product meet customer needs' (P_4) is highly related to another measure, namely, 'customer needs' (M_5) in the marketing category, as their Pearson Correlation Coefficient (0.998) is very high. The results from the cluster analysis confirm this assertion, as P_4 and M_5 are grouped as one evaluation criterion.

4.3 Weights calculation

Once the decision model is developed, it is essential to know how important each criterion is. Here, the importance weights were calculated using Prelec (1998) PWF discussed in Section 3.3. First, $w(p)$ was calculated based on the probabilities of relevant comments with respect to the concepts included in the associated criterion/sub-criterion, as described in Equation 1. The weights for evaluation criteria/sub-criteria were then derived using Equation 2. The value of PWF parameter α is first set as 0.5 in this section, which is the middle of its standard range ($0<\alpha<1$). Nevertheless, different values of parameter α will be varied in the later section to examine its impact on the NPD evaluation decision. The weight results for all the evaluation criteria/sub-criteria are displayed in Table 4. Not surprisingly, the criteria/sub-criteria containing the concepts that are regularly motioned by consumers in the social media site, such as C_{34}, C_{341}, C_{342}, and $C_{343,}$ carry higher weights.

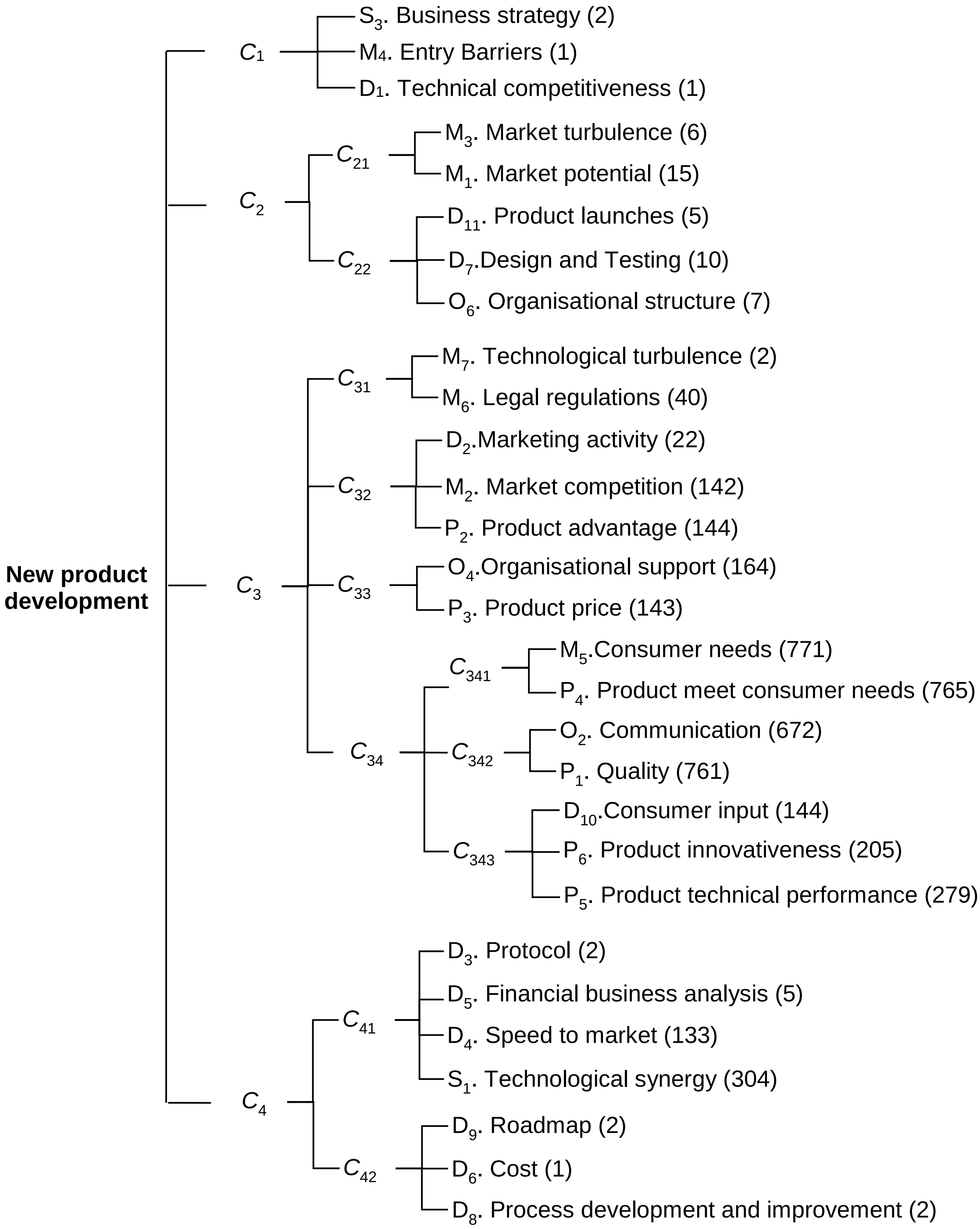

Figure 2. Hierarchical decision model for new product development evaluation

4.4 Evaluation of alternative designs

To demonstrate how MCDA methods can be applied to select alternatives or to make decisions, four alternative design options are considered. While the four designs share some common features, for instance the Android operating system, processor and high resolution screen display, they also display some differences, as described in Table 5.

Table 4. Weights for the evaluation criteria/sub-criteria

	Weights		Weights		Weights
C_1	0.056				
C_2	0.125	C_{21}	0.052		
		C_{22}	0.074		
C_3	0.626	C_{31}	0.053		
		C_{32}	0.114		
		C_{33}	0.085		
		C_{34}	0.374	C_{341}	0.120
				C_{342}	0.118
				C_{343}	0.136
C_4	0.192	C_{41}	0.134		
		C_{42}	0.058		

Table 5. Key design features between the four design options

Design options	Key differences
Design 1	Design 1 is an updated version of the previous model, with a new Android operating system, an improved processor and a higher-resolution screen display, but with no other new features.
Design 2	Design 2 adopts the latest processor technology that provides faster GPU and CPU performance. It enables users to do more, longer and faster than before, but does not add other new features.
Design 3	In addition to the core updated functions, Design 3 also includes other key features that many consumers demand, such as longer battery life and an enhanced camera function that makes it easy to take rich photos and videos.
Design 4	While sharing similar features, Design 4 has subdued processing performance and a less powerful camera. But it is a cheaper option.

Three academics with expert knowledge in operations management, engineering and marketing were asked to complete the questionnaires required for the evaluation of alternative design options, using AHP, fuzzy AHP and TOPSIS respectively. For AHP and fuzzy AHP, the consistency ratio of each judgement was also calculated and checked, to ensure that it is lower than or equal to 0.1. The analysis steps involved in each method are provided in the appendix, and the final results are described in Table 6.

Although different aggregated indexes were produced, the same ranking order was obtained for all three approaches. Both AHP and TOPSIS showed their effectiveness in solving MCDA problems and computational simplicity. Despite the benefits of fuzzy AHP, claimed by many academics as its ability to deal with the ambiguity and imprecision inherent in the process of mapping the perceptions of decision-makers (Huang *et al.*, 2008; Wang *et al.*, 2008; Krohling and Campanharo, 2011; Chan *et al.*, 2013), both AHP and fuzzy AHP generate very similar set of aggregated index (AI) values as displayed in Table 6.

Table 6. Evaluation results from three different MCDA approaches

	AHP		FAHP		TOPSIS	
	AI	Rankings	AI	Rankings	AI (Cc_i)	Rankings
Design 1	0.189	4	0.185	4	0.224	4
Design 2	0.228	3	0.224	3	0.260	3
Design 3	0.300	1	0.303	1	0.857	1
Design 4	0.282	2	0.287	2	0.590	2

4.5 Effect of the PWF parameter, α

Since the weighting of decision criteria often plays an important role in MCDA problems, further analysis was conducted to examine the influence of probability weighting function parameter α on the evaluation result. Different sets of parameter values were used in the analysis, and the results are presented in Table 7.

The analysis results show that if the variation of the PWF parameter values is not set at too extreme a value, it has little impact on the selection decision of the alternative design options. To be precise, Table 7 indicates that the same decision remains unchanged if α is varied from 0.3 to 0.7 on all MCDA methods. In contrast, it will affect the ranking order if the parameter α significantly deviates from the chosen middle value (i.e. 0.5). In Table 7, this occurs when α is equal to 0.3 and 0.8. More specifically, the results suggest that decision-makers overweigh low probabilities and underweigh high probabilities if the parameter value is low (close to 0). In contrast, the results suggest that decision-makers underweigh low probabilities and overweigh high probabilities if the parameter value is high (close to 1). The recommendation is that α should be set close to 0.5 unless there is a good reason to under- or over-weigh either low or high probabilities.

Table 7. Sensitivity analysis of the PWF parameter

PWF Parameter	Designs	AHP		FAHP		TOPSIS	
		AI	Rankings	AI	Rankings	AI (Cc_i)	Rankings
a=0.2	Design 1	0.189	4	0.192	4	0.149	4
	Design 2	0.208	3	0.213	3	0.151	3
	Design 3	0.299	2	0.297	2	0.818	1
	Design 4	0.304	1	0.297	1	0.692	2
a=0.3	Design 1	0.189	4	0.192	4	0.167	4
	Design 2	0.211	3	0.217	3	0.175	3
	Design 3	0.300	1	0.297	1	0.826	1

	Design 4	0.300	2	0.294	2	0.670	2
a=0.4	Design 1	0.187	4	0.191	4	0.191	4
	Design 2	0.217	3	0.221	3	0.210	3
	Design 3	0.301	1	0.298	1	0.839	1
	Design 4	0.295	2	0.289	2	0.638	2
a=0.5	Design 1	0.185	4	0.189	4	0.224	4
	Design 2	0.224	3	0.228	3	0.260	3
	Design 3	0.303	1	0.300	1	0.857	1
	Design 4	0.287	2	0.282	2	0.590	2
a=0.6	Design 1	0.183	4	0.187	4	0.266	4
	Design 2	0.235	3	0.237	3	0.333	3
	Design 3	0.305	1	0.302	1	0.882	1
	Design 4	0.277	2	0.273	2	0.523	2
a=0.7	Design 1	0.180	4	0.185	4	0.312	4
	Design 2	0.248	3	0.249	3	0.428	3
	Design 3	0.309	1	0.306	1	0.914	1
	Design 4	0.264	2	0.260	2	0.432	2
a=0.8	Design 1	0.176	4	0.182	4	0.359	3
	Design 2	0.264	2	0.263	2	0.542	2
	Design 3	0.313	1	0.309	1	0.947	1
	Design 4	0.247	3	0.245	3	0.321	4

5. Conclusions

5.1 Contributions of this study

Application of social media platforms for business purposes is continuously growing. Consumers are encouraged to exchange their views and opinions regarding products and services via such channels. This generates a huge volume of potentially useful data. Unfortunately, the true value of such data has not been realised, and thus companies potentially miss out on opportunities to gain competitive advantages and ensure sustainable growth in highly competitive markets.

Utilisation of social media data appears to be a challenge for both researchers and practitioners, who until now had no effective approach to analyse it. This study aims to address this challenge, proposing a comprehensive methodology which, while drawing from a number of research disciplines, integrates multiple research methods to examine how the social media data can be leveraged for OM decision-making (e.g. NPD). The proposed approach considers the ‘consumer’s voice’ while making key strategic decisions preserving their ‘sense of empowerment’. This is the first study to address this issue.

Furthermore, this study opens avenues for a new data-driven research stream in the OM research field (Delage and Ye, 2010; Simchi-Levi, 2014). While data-driven research is not a new approach (see, for example, Braca *et al.* (1997)), it was not possible to apply such approaches easily in the past. This study provides a solution to this problem while utilising data-driven research for social media data analysis. This application of data-driven research is novel and of particular importance today, due to the growing amount of available data and the enhancement in computational power derived from the advancement of digital technology.

Application of the proposed approach also leads to theoretical as well as practical contributions, thus bridging the gap between theoretical research and practical needs. For example, in the case study in this research project, the extension of the proposed model is highly practical, mainly due to the nature of the data source, which is customer-oriented.

5.2 Implications and future research

The purpose of this study was to develop a new approach to facilitate the utilisation of social media data to support OM decisions. By fulfilling this purpose, the study makes significant contributions to several important and interrelated research fields.

First, acquiring information from users/customers about their preferences, requirements and needs is often emphasized as a prerequisite for successful NPD (Katila and Ahuja, 2002; Piller and Walcher, 2006). Traditionally, the collection of such information was costly in terms of both time and money. The proposed approach allows organisations to be more economical, through the utilisation of data freely available online. This research proposes an effective and efficient approach to social media data analysis for decision-making processes.

Second, although in this study the application of the proposed approach illustrated in the case study focuses on NPD, there is a similar demand for social media data utilisation in other management areas, including product and service innovations, market research and orientation, and organisational learning, where the 'consumer's voice' needs to be heard. Our study explores the capabilities and true value of a mixed-method approach in handling social media data.

Despite the benefits of the proposed approach above, this research has limitations which could lead to future research opportunities. For example, whilst this research develops a mixed-method approach to analyse social media data for OM, there are also opportunities to apply it to other management areas as discussed above. This may require the incorporation of other methods, subject to the nature of the management problem. Moreover, although the probability weighting method has proven to be a more effective weighting method as it is used for calculating weights based on the social media data, decision makers have to make subjective judgements while deciding which alternative design to select. Therefore, one future research direction is to consider a more data-driven evaluation technique, such as Data Envelopment Analysis, to compare alternative design options.

References:

Akar, E., B. Topçu. 2011. An examination of the factors influencing consumers' attitudes toward social media marketing. *Journal of Internet Commerce* **10**(1) 35-67.

Anderson, E.G., N.R. Joglekar. 2005. A hierarchical product development planning framework. *Production and Operations Management* **14**(3) 344-361.

Bastic, M. 2004. Success factors in transition countries. *European Journal of Innovation Management* **7**(1) 65-79.

Boer, F.P. 1998. Traps, pitfalls and snares in the valuation of technology. *Research Technology Management* **41** 45-54.

Braca, J., J. Bramel, B. Posner, D. Simchi-Levi. 1997. A computerized approach to the New York City school bus routing problem. *IIE transactions* **29**(8) 693-702.

Brewerton, P., L. Millward. 2001. *Organisational research methods*, Sage, London.

Buckley, J. 1985. Fuzzy hierarchical analysis. *Fuzzy Sets and Systems* **17** 233-247.

Cankurtaran, P., F. Langerak, A. Griffin. 2013. Consequences of New Product Development Speed: A Meta-Analysis. *Journal of Product Innovation Management* **30**(3) 465-486.

Carley, K. 1993. Coding choices for textual analysis: A comparison of content analysis and map analysis. *Sociological methodology* **23** 75-126.

Carrillo, J.E. 2005. Industry clockspeed and the pace of new product development. *Production and Operations Management* **14**(2) 125-141.

Chamodrakas, I., N. Alexopoulou, D. Martakos. 2009. Customer evaluation for order acceptance using a novel class of fuzzy methods based on TOPSIS. *Expert Systems with Applications* **36**(4) 7409-7415.

Chan, H.K., X. Wang, G. White, Y. Nick. 2013. An Extended Fuzzy AHP approach for the evaluation of green product designs. *IEEE Transactions on Engineering Management* **60**(2) 327-339.

Chen, J., R.R. Reilly, G.S. Lynn. 2005. The impacts of speed-to market on new product success: The moderating effects of uncertainty. *IEEE Transactions on Engineering Management* **52**(2) 199-212.

Cho, J., J. Lee. 2013. Development of a new technology product evaluation model for assessing commercialization opportunities using Delphi method and fuzzy AHP approach. *Expert System with Applications* **40**(13) 5314-5330.

Cooper, R.G. 1994. New products: The factors that drive success. *International Marketing Review* **11**(1) 60-76.

Cooper, R.G., E.J. Kleinschmidt. 1994. Determination of timeliness in product development. *Journal of Product Innovation Management*, **10**, 112-125.

Cooper, R.G., E.J. Kleinschmidt. 1995. Benchmarking the firm's critical success factors in new product development. *Journal of product innovation management* **12**(5) 374-391.

Davies, J., N. Joglekar. 2013. Supply Chain Integration, Product Modularity, and Market Valuation:

Evidence from the Solar Energy Industry. *Production and Operations Management* **22**(6) 1494-1508.

Delage, E., Y. Ye. 2010. Distributionally robust optimization under moment uncertainty with application to data-driven problems. *Operations Research* **58**(3) 595-612.

Denecke, K., W. Nejdl. 2009. How valuable is medical social media data? Content analysis of the medical web. *Information Sciences* **179**(12) 1870-1880.

Ernst, H. 2002. Success factors of new product development: a review of the empirical literature. *International Journal of Management Reviews* **4**(1) 1-40.

Ellison, N.B. 2007. Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication* **13**(1) 210-230.

Fink, A. 1998. *Conducting research literature reviews: from paper to the internet*, Sage, Thousand Oaks.

Flynn, B.B., S. Sakakibara, R.G. Schroeder, K.A. Bates, E.J. Flynn. 1990. Empirical research methods in operations management. *Journal of operations management* **9**(2) 250-284.

Fortun, M., S.S. Schweber. 1993. Scientists and the legacy of World War II: The case of operations research (OR). *Social Studies of Science* **23**(4) 595-642.

Fuchs, C., M. Schreier. 2011. Customer empowerment in new product development. *Journal of Product Innovation Management* **28**(1) 17-32.

Füller, J., M. Bartl, H. Ernst, H. Mühlbacher. 2006. Community based innovation: How to integrate members of virtual communities into new product development. *Electronic Commerce Research* **6**(1) 57-73.

Gruner, K.E., C. Homburg. 2000. Does customer interaction enhance new product success? *Journal of business research* **49**(1) 1-14.

Gu, B., Q. Ye. 2014. First Step in Social Media-Measuring the Influence of Online Management Responses on Customer Satisfaction. *Productions and Operations Management* **23**(4) 570-582.

Hanna, R., A. Rohm, V.L. Crittenden. 2011. We're all connected: The power of the social media ecosystem. *Business Horizons* **54**(3) 265-273.

Henard, D.H., D.M. Szymanski. 2001. Why some new products are more successful than others. *Journal of marketing Research* **38**(3) 362-375.

Hendricks, K.B., V.R. Singhal. 1997. Delays in new product introductions and the market value of the firm: The consequences of being late to the market. *Management Science* **43**(4) 422-436.

Hoyer, W.D., R. Chandy, M. Dorotic, M. Krafft, S.S. Singh. 2010. Consumer cocreation in new product development. *Journal of Service Research* **13**(3) 283-296.

Hsieh, H.F., S.E. Shannon. 2005. Three approaches to qualitative content analysis. *Qualitative health research* **15**(9) 1277-1288.

Huang, C., P. Chu, Y. Chiang. 2008. A fuzzy AHP application in government-sponsored R&D project selection, *Omega* **36** 1038-1052.

Hultink, E.J., A. Griffin, S. Hart, H.S. Robben. 1997. Industrial new product launch strategies and product development performance. *Journal of Product Innovation Management* **14**(4) 243-257.

Hwang, C.L., K. Yoon. 1981. *Multiple attributes decision making methods and applications*, Springer, Berlin.

Im, S., J.P. Jr. Workman. 2004. Market orientation, creativity, and new product performance in high-technology firms. *Journal of Marketing* **68**(2) 114-132.

Jang, H.J., J. Sim, Y. Lee, O. Kwon. 2013. Deep sentiment analysis: Mining the causality between personality-value-attitude for analyzing business ads in social media. *Expert Systems with Applications* **40**(18) 7492-7503.

Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society* **47**(2) 263-291.

Katila, R., G. Ahuja. 2002. Something old, something new: a longitudinal study of search behaviour and new product introduction. *Academy of Management Journal* **45** 1183-1194.

Krishnan, V., K.T. Ulrich. 2001. Product development decisions: A review of the literature. *Management Science* **47**(1) 1-21.

Krohling, R.A., V.C. Campanharo. 2011. Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea. *Expert Systems with Applications* **38**(4) 4190-4197.

Labrecque, L.I., C. Mathwick, T.P. Novak, C.F. Hofacker. 2013. Consumer Power: Evolution in the Digital Age. *Journal of Interactive Marketing* **27**(4) 257-269.

Li, Y.M., C.Y. Lai, C.W. Chen. 2011. Discovering influencers for marketing in the blogosphere. *Information Sciences* **181**(23) 5143-5157.

Mallick, D.N., R.G. Schroeder. 2005. An integrated framework for measuring product development performance in high technology industries. *Production and Operations Management* **14**(2) 142-158.

Malthouse, E.C., M. Haenlein, B. Skiera, E. Wege, M. Zhang. 2013. Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House. *Journal of Interactive Marketing* **27**(4) 270-280.

McGrath, R.G. 1997. A Real Options Logic for Initiating Technology Positioning Investments. *Academy of Management Review* **22**(4) 974-996.

Mishra, S., K. Dongwook, H.L. Dae. 1996. Factors affecting new product success: cross-country comparisons. *Journal of Product Innovation Management* **13**(6) 530-550.

Montoya-Weiss, M.M., R. Calanone. 1994. Determinants of new product performance: a review and meta-analysis. *Journal of Product Innovation Management* **11** 397-417.

Mullens, M.A., M. Arif, R.L. Armacost, T.A. Gawlik, R.L. Hoekstra. 2005. Axiomatic based decomposition for conceptual product design. *Production and Operations Management* **14**(3) 286-300.

Nambisan, S. 2002. Designing virtual customer environments for new product development: Toward a theory. *Academy of Management Review* **27**(3) 392-413.

Padmanabhan, V., S. Rajiv, K. Srinivasan. 1997. New products, upgrades, and new releases, a rationale for sequential product introduction. *Journal of Marketing Research* **34**(4) 456-472.

Peng, T., L. Liu. 2015. A novel incremental conceptual hierarchical text clustering method using CFu-tree. *Applied Soft Computing* **27** 269-278.

Piller, F.T., D. Walcher. 2006. Toolkits for idea competitions: a novel method to integrate users in new product development. *R&D Management* **36**(3) 307-318.

Prelec, D. 1998. The probability weighting function. *Econometrica* **66**(3) 497-527.

Pun, K.F., K.S. Chin. 2005. Online assessment of new product development performance: an approach. *Total Quality Management and Business Excellence* **16**(2) 157-169.

Pun, K.F., K.S. Chin, M.Y.R. Yiu. 2010. An AHP approach to assess new product development performance: An exploratory study. *International Journal of Management Science and Engineering Management* **5**(3) 210-218.

Saaty, T.L. 1980. *The analytic hierarchy process*, McGraw-Hill Press, New York.

Sawhney, M., G. Verona, E. Prandelli. 2005. Collaborating to create: The Internet as a platform for customer engagement in product innovation. *Journal of Interactive Marketing* **19**(4) 4-17.

Scudder, G.D., C.A. Hill. 1998. A review and classification of empirical research in operations management. *Journal of Operations Management* **16**(1) 91-101.

Seuring, S., M. Muller. 2008. From literature review to a conceptual framework for suitable supply chain management. *Journal of Cleaner Production* **16** 1699-1710.

Simchi-Levi, D. 2014. OM Forum-OM Research: From Problem-Driven to Data-Driven Research. *Manufacturing & Service Operations Management* **16**(1) 2-10.

Singhal, K., J. Singhal. 2012. Imperatives of the science of operations and supply-chain management. *Journal of Operations Management* **30**(3) 237-244.

Slater, S.F., J.C. Narver. 1998. Research notes and communications customer-led and market-oriented: let’s not confuse the two. *Strategic Management Journal* **19**(10) 1001-1006.

Souder, W.E., X.M. Song. 1998. Analyses of US and Japanese management processes associated with new product success and failure in high and low familiarity markets. *Journal of Product Innovation Management* **15**(3) 208-223.

Tranfield, D., D. Denyer, P. Smart. 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management* **14** 207-222.

Tripathy, A., S.D. Eppinger. 2013. Structuring Work Distribution for Global Product Development Organizations. *Productions and Operations Management* **22**(6) 1557-1575.

Trusov, M., R.E. Bucklin, K.H. Pauwels. 2009. Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal of Marketing* **73**(5) 90-102.

Tversky, A., D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty* **5**(4) 297-323.

Van laarhoven, P.J.M., W. Pedrycz. 1983. A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems* **11** 229-241.

Von Hippel, E. 1986. Lead users: a source of novel product concepts. *Management Science* **32**(7) 791-805.

Wang, Y.-M., Y. Luo, Z. Hua. 2008. On the extent analysis method for fuzzy AHP and its applications. *European Journal of Operational Research* **186**(2) 735-747.

Wu, G., R. Gonzalez. 1996. Curvature of the probability weighting function. *Management Science* **42**(12) 1676-1690.

Xiang, Z., U. Gretzel. 2010. Role of social media in online travel information search. *Tourism Management* **31**(2) 179-188.

Appendix A

A1. Design evaluation using AHP

The first step is to formulate synthetic pairwise comparison matrices. Using evaluation criterion C_1 as an example, the synthetic pairwise comparison matrix is displayed in Table A1.

Table A1. AHP pairwise comparison matrix for alternative designs with respect to C_1

	Design 1	Design 2	Design 3	Design 4
Design 1	1.000	1.587	0.437	0.382
Design 2	0.630	1.000	0.437	0.397
Design 3	2.289	2.289	1.000	0.794
Design 4	2.621	2.520	1.260	1.000

Note: the consistency ratio CI/RI=0.012

Following the AHP calculation outlined by Satty (1980), the relative performance ratings of four alternative designs with respect to C_1 are obtained as R_1=(0.164, 0.131, 0.322, 0.383). By repeating the calculation for other criteria, the performance ratings of alternative designs with respect to other evaluation criteria/sub-criteria can be obtained, as shown in Table A2. An aggregated index (AI) is then calculated by aggregating the performance ratings of each design, with respect to all evaluation criteria and comparative weightings between the criteria/sub-criteria. The highest value of aggregated index, in this case Design 3, is the best design option for the company to select.

Table A2. Evaluation results for four alternative designs using AHP

	C_1	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{341}	C_{342}	C_{343}	C_{41}	C_{42}	AI	Rank
Weights	0.056	0.052	0.074	0.053	0.114	0.085	0.120	0.118	0.136	0.134	0.058		
Design 1	0.164	0.155	0.351	0.186	0.230	0.135	0.190	0.144	0.171	0.167	0.161	**0.185**	**4**
Design 2	0.131	0.148	0.189	0.122	0.119	0.194	0.294	0.427	0.228	0.222	0.213	**0.224**	**3**
Design 3	0.322	0.297	0.109	0.311	0.261	0.268	0.343	0.303	0.335	0.363	0.362	**0.303**	**1**
Design 4	0.383	0.400	0.351	0.381	0.390	0.404	0.173	0.125	0.267	0.248	0.264	**0.287**	**2**

A2. Design evaluation using fuzzy AHP

Similar to AHP, the first step is to formulate fuzzy synthetic pairwise comparison matrices. Table A3 displays the fuzzy synthetic pairwise comparison matrix of the criterion C_1, as an example.

Table A3. Fuzzy AHP pairwise comparison matrix for alternative designs with respect to C_1

	Design 1	Design 2	Design 3	Design 4
Design 1	(1, 1, 1)	(1, 1.587, 2.080)	(0.303, 0.437, 0.794)	(0.275, 0.382, 0.630)
Design 2	(0.481, 0.630, 1)	(1, 1, 1)	(0.303, 0.437, 0.794)	(0.281, 0.397, 0.693)
Design 3	(1.260, 2.289, 3.302)	(1.260, 2.289, 3.302)	(1, 1, 1)	(0.693, 0.794, 1)
Design 4	(1.587, 2.621, 3.634)	(1.442, 2.520, 3.557)	(1, 1.260, 1.442)	(1, 1, 1)

The next step is to calculate the fuzzy geometric mean ($\tilde{r}_i$) and fuzzy ratings ($\tilde{R}_i$) of four alternative designs. First, the fuzzy ratings of dimensions for the owners group are given as:

$$\tilde{r}_1 = (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \tilde{a}_{13} \otimes \tilde{a}_{14})^{\frac{1}{4}}$$

$$= \left((1 \times 1 \times 0.30 \times 0.28)^{1/4}, (1 \times 1.59 \times 0.44 \times 0.38)^{1/4} (1 \times 2.08 \times 0.79 \times .63)^{1/4}\right)$$

$$= (0.537, 0.717, 1.010)$$

Similarly, we can obtain the remaining $\tilde{r}_i$, that is:

$$\tilde{r}_2 = (0.450, 0.575, 0.861)$$

$$\tilde{r}_3 = (1.024, 1.428, 1.817)$$

$$\tilde{r}_4 = (1.230, 1.698, 2.078)$$

The ratings of each dimension can be calculated as follows:

$$\widetilde{R_1} = \tilde{r}_1 \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \oplus \tilde{r}_4)^{-1}$$

$$= (0.537, 0.717, 1.010) \otimes \left(\frac{1}{1.010 + \cdots + 2.078}, \frac{1}{0.717 + \cdots + 1.698}, \frac{1}{0.537 + \cdots + 1.230}\right)$$

$$= (0.093, 0.162, 0.312)$$

Likewise, the remaining fuzzy ratings values of each design can be obtained. The results are displayed in Table A4.

Table A4. Performance ratings of alternative designs with respect to *C*1

	(*LRi*, *MRi*, *URi*)	Non-fuzzy weights	Normalised weights
$\tilde{R}_1$	(0.093, 0.162, 0.312)	0.189	0.170
$\tilde{R}_2$	(0.078, 0.130, 0.266)	0.158	0.142
$\tilde{R}_3$	(0.178, 0.323, 0.561)	0.354	0.318
$\tilde{R}_4$	(0.213, 0.384, 0.641)	0.413	0.371

The non-fuzzy value was obtained through the Centre-of-Area method. Similarly, the performance ratings of alternative designs with respect to other evaluation criteria/sub-criteria can be obtained. AIs for all the four alternative designs are then calculated by aggregating the performance ratings of each design with respect to all evaluation criteria. The results are illustrated in Table A5, in which Design 3 has the highest index value.

Table A5. Evaluation results for four alternative designs using fuzzy AHP

	C_1	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{341}	C_{342}	C_{343}	C_{41}	C_{42}	AI	Rank
Weights	0.056	0.052	0.074	0.053	0.114	0.085	0.120	0.118	0.136	0.134	0.058		
Design 1	0.170	0.159	0.338	0.186	0.232	0.144	0.203	0.148	0.176	0.171	0.163	0.185	4
Design 2	0.142	0.157	0.207	0.132	0.123	0.203	0.288	0.416	0.229	0.231	0.221	0.224	3
Design 3	0.318	0.298	0.117	0.309	0.264	0.263	0.332	0.306	0.333	0.354	0.354	0.303	1
Design 4	0.371	0.387	0.338	0.373	0.380	0.391	0.176	0.130	0.263	0.245	0.262	0.287	2

A3. Design evaluation using TOPSIS

First, the evaluations from all three experts are incorporated to form the decision matrix, as illustrated in the left-hand side of Table A6 for TOPSIS evaluation. The weighted normalized decision matrix is obtained as shown in the right-hand side of Table A6.

Table A6. Decision matrix and weighted normalised decision matrix for TOPSIS evaluation.

	Decision Matrix for TOPSIS evaluation				Weighted normalized decision matrix			
	Design 1	**Design 2**	**Design 3**	**Design 4**	**Design 1**	**Design 2**	**Design 3**	**Design 4**
C_1	5.00	4.33	6.33	6.67	0.042	0.037	0.054	0.056
C_{21}	5.00	4.67	6.33	6.67	0.039	0.036	0.049	0.052
C_{22}	6.33	5.33	4.33	6.33	0.070	0.059	0.048	0.070
C_{31}	4.67	3.33	6.00	6.33	0.037	0.027	0.048	0.050
C_{32}	5.33	4.00	5.67	6.00	0.091	0.068	0.097	0.102
C_{33}	4.00	5.00	5.00	6.00	0.051	0.064	0.064	0.077
C_{341}	5.00	5.67	6.00	4.67	0.090	0.102	0.108	0.084
C_{342}	4.33	6.33	5.67	4.00	0.077	0.112	0.100	0.071
C_{343}	4.67	5.33	6.00	5.00	0.095	0.109	0.122	0.102
C_{41}	4.67	5.00	6.33	5.33	0.094	0.100	0.127	0.107
C_{42}	4.33	4.67	6.00	5.33	0.038	0.041	0.052	0.047

After aggregating the weighted normalized performance rating of sub-criteria into their associated decision criteria, the ideal solution (A^+) and the negative ideal solution (A^-) for each decision criterion can be determined. Then, the distances (d^+ and d^-) between positive ideal solution and negative ideal solution for each design option can be calculated by the area compensation method. The relative closeness index for each design is calculated by combining the difference distances d^+ and d^-. The four designs are ranked according to the relative closeness index values. The results are illustrated in Table A7 and, again, Design 3 tops the ranking order.

Table A7. Evaluation results for four alternative designs using TOPSIS

	Design 1		**Design 2**		**Design 3**		**Design 4**	
	d+	d-	d+	d-	d+	d-	d+	d-
C_1	0.014	0.000	0.020	0.000	0.003	0.017	0.000	0.020
C_2	0.013	0.000	0.027	0.000	0.025	0.002	0.000	0.027
C_3	0.098	0.040	0.057	0.040	0.000	0.098	0.053	0.045
C_4	0.048	0.010	0.038	0.010	0.000	0.048	0.026	0.022
SUM	0.173	0.050	0.142	0.050	0.028	0.165	0.079	0.113
Cci	0.224		0.260		0.857		0.590	
Rank	4		3		1		2	